DATA AND METHODS

Data

Data are from the 1998 through 2001 Food Security Supplements to the Current Population Survey (CPS-FSS).[4] The CPS-FSS uses an 18-item scale to classify households as food secure, food insecure without hunger, or food insecure with hunger over the past 12 months. Because there were two Food Security Supplements administered during 2001 (April and December), we have a total of five panels of data.

We limit our main analysis sample to households with children, because food insecurity is most prevalent among these households, and because the determinants of food insecurity may differ among different household types. In particular, some of the contextual variables in our analysis describe nutrition assistance programs targeting children, such as the school breakfast program and summer food program. Our sample includes a total of 70,942 households.

These data are supplemented with state-level data describing various aspects of the food security infrastructure. Those data are described in more detail below.

Models

Because our data consist of households clustered within states (or more precisely, within contexts that vary by state and year), we use hierarchical modeling for our analyses (Raudenbush and Bryk, 2002). Hierarchical modeling is ideally suited to the analysis of data with a nested structure, in which both individual and contextual characteristics are thought to affect outcomes of interest (Osborne, 2000). With nested data, dependency among observations is potentially problematic, and ordinary least squares (OLS) estimates can yield both inefficient parameter estimates and biased standard errors. With

[4]For detailed discussion of the CPS sample design, see http://www.bls.census.gov/cps/bmethdoc.htm.

hierarchical (or multilevel) models, some or all of the coefficients are treated as randomly varying by context, and these random coefficients can be explicitly modeled as functions of contextual characteristics. Such models allow errors to be dependent within contexts, thus implicitly controlling for unmeasured contextual characteristics that are correlated with the dependent variable.

Hierarchical models are particularly useful in formulating and empirically testing hypotheses about how contextual characteristics may affect household-level outcomes, both directly (in the case of random intercepts) and by moderating the impact of relevant household attributes (in the case of random slopes). Of course, one can also explore contextual effects using fixed-effects models that include dummy variables for each unique context; however, such models do not allow one to explore how specific contextual characteristics affect the outcome. Alternatively, one can include contextual characteristics in an OLS model, while ignoring residual within-group correlation. Hierarchical models, in contrast, allow for the estimation of the effects of specific contextual characteristics, while also controlling for unmeasured differences across contexts that are correlated with the outcome of interest. Furthermore, such models allow the analyst to obtain context-specific parameter estimates by augmenting within-context information with evidence from the broader sample (that is, by 'borrowing strength' from the full sample).

We present both a random intercept model and a random slopes model. Our random intercept model can be written as follows:

Level 1 Model

$$\text{Log}[p_{ij}/(1-p_{ij})] = \beta_{0j} + \beta_{10}X_{1ij} + \beta_{20}X_{2ij} + \ldots + \beta_{n0}X_{nij} \quad (1)$$

Level 2 Model

$$\beta_{0j} = \gamma_{00} + \gamma_{01}W_{1j} + \ldots + \gamma_{0q}W_{qj} + \mu_{0j} \quad (2),$$

Where p_{ij} is the probability that household *i* in state-year *j* is food insecure;

$\mathbf{X}_{ij}$ is a vector of sociodemographic characteristics of household *i* in state-year *j*;

$\mathbf{W}_j$ is a vector of characteristics representing the food security infrastructure in state-year *j*;

and u_{0j} is a random normal variable with mean of 0 and variance τ_{00}.

Note that the Level 2 unit is the state-year. Conceptually, this reflects the fact that the relevant contextual characteristics vary by state, and within states vary over time. Thus, the households in our sample can be thought of as nested within a total of 255 different contexts (50 states and the District of Columbia, each observed in five different periods).

In the Level 1 model (presented in Equation 1), the log-odds of household-level food insecurity is expressed as a function of various characteristics of an individual household *i*. The intercept from this model, $\beta_{0j,}$ is a random variable that varies among contexts. The slopes, β_{10} through β_{n0} , are assumed to be constant.

In the Level 2 model, the intercept from Level 1 (β_{0j}) is expressed as a function of context-specific variables $\mathbf{W_j}$ (Equation 2). These variables represent various components of the food security infrastructure in each state and year. The model implies, then, that there are systematic differences in food security across state-years that can be explained in part by characteristics of the state context. Substituting Equation 2 into Equation 1 results in a single prediction equation, in which errors are dependent within state-years. [5] The dependence of the errors is a key feature of this type of model, and has the effect of controlling for unmeasured contextual characteristics that are correlated with the outcome.

The model parameters do not include each of the state-specific intercepts β_{0j}, but rather, estimates of the mean intercept γ_{00} and the variance of the Level 2 error $\mu_{0j.}$ The individual intercepts can, however, be predicted, as can the level two errors, μ_{0j} . We discuss this in more detail below.

We also present a random slopes model, in which household income coefficients are assumed to be random, context-dependent variables. Our model can be expressed as follows:

[5] Although our modeling approach explicitly allows for dependence among observations in each state-year context, it does not address potential dependence among observations in different years for the same state. Because of this, we may be underestimating true standard errors.

Level 1 Model

$$\mathrm{Log}[p_{ij}/(1\text{-}p_{ij})] = \beta_{0j} + \beta_{1j}X_{1ij} + \beta_{2j}X_{2ij} + \beta_{3j}X_{3ij} + \beta_{4j}X_{4ij} + \beta_{50}X_{5ij} + \beta_{60}X_{6ij} + \ldots + \beta_{n0}X_{nij} \quad (3)$$

Level 2 Model

$$\beta_{0j} = \gamma_{00} + \gamma_{01}W_{1j} + \ldots + \gamma_{0q}W_{qj} + \mu_{0j} \quad (2)$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11} W_{1j} + \ldots \gamma_{1q}W_{qj} + \mu_{1j} \quad (4)$$

$$\beta_{2j} = \gamma_{20} + \gamma_{21} W_{1j} + \ldots \gamma_{2q}W_{qj} + \mu_{2j} \quad (5)$$

$$\beta_{3j} = \gamma_{30} + \gamma_{31} W_{1j} + \ldots \gamma_{3q}W_{qj} + \mu_{3j} \quad (6)$$

$$\beta_{4j} = \gamma_{40} + \gamma_{41} W_{1j} + \ldots \gamma_{4q}W_{qj} + \mu_{4j} \quad (7)$$

where u_{0j}, u_{1j}, u_{2j}, u_{3j}, and u_{4j} are random normal variables with means of 0 and variances τ_{00}, τ_{11}, τ_{22}, τ_{33}, and τ_{44}.

Here, X_{1ij} through X_{4ij} denote four income categories: poor, near poor (1.0 to 1.3 times the poverty line), low income (1.3 to 1.85 times the poverty line), and missing income (where the reference category is above 1.85 times poverty line)[6]. This model allows us to examine whether aspects of the state food security infrastructure moderate the relationship between household income and food security. The model reflects our assumption that contextual characteristics are of particular relevance to economically vulnerable households' efforts to maintain food security. In particular, we note that at least some aspects of the food security infrastructure—such as the availability and accessibility of nutrition assistance programs—are only relevant to lower-income households.

Our primary focus is on factors linked to food insecurity. However, we also estimate comparable models in which food insecurity with hunger—a severe level of food insecurity—is the dependent variable.

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[6] These classifications are linked to household eligibility for food assistance programs. Children from poor or near-poor households may be eligible for free meals and for Food Stamps. Children from low-income households may be eligible for reduced-price meals.

Measures

Level 1 Measures

We include the following household-level variables in our model (see Table 1 for means and standard deviations): Income-to-poverty ratio (and ratio squared), highest education level in household, race/ethnicity of household head, home ownership, location (central city, other metropolitan, or nonmetropolitan), household structure (single mother, single father, couple, other), number of children, presence of employed person(s) in household, presence of elderly person(s) in household, presence of disabled person(s) in household, and presence of noncitizens in household. All continuous variables are entered as mean-centered variables in our models.

Level 2 Measures

We include a variety of Level 2 variables representing components of the food security infrastructure. For simplicity, we use the term "state-level variables" to refer to these variables. Note, however, that in most cases these variables vary by both state (50 states and Washington, D.C.) and time (five different time periods corresponding to the food security reference period of the five CPS-FSS panels). Thus, our Level 2 measures describe the context within which households are grouped, where that context is both state and time dependent. In a few instances, we have only a single state measure and apply it to all years. When the relevant reference year spans two calendar years, we construct the measures by prorating the values for each of the years. Variable means and standard deviations are shown in Table 1. As with the Level 1 variables, continuous variables are mean-centered in the models.

Availability and Accessibility of Federal Food Assistance and Nutrition Programs. Unlike research seeking to link a household's program participation to food security or other nutritional outcomes, our approach is to treat food assistance programs as components of the food security infrastructure. We are interested in the extent to which differences (across states and over time) in the availability and

TABLE 1
Variable Means and Standard Deviation

	Mean	*SD*
Dependent Variables		
Food insecurity	.16	.36
Food insecurity with hunger	.04	.19
Level 1 Variables		
Income		
Income/poverty ratio	2.68	1.40
Ratio squared	9.32	8.08
Missing income	0.08	0.27
Education		
High school	0.26	0.44
Some college	0.33	0.47
College degree or more	0.34	0.47
Race		
Black	0.11	0.32
Hispanic	0.11	0.32
American Indian	0.02	0.12
Asian	0.04	0.19
Housing Tenure		
Rent	0.29	0.45
Live without paying	0.02	0.13
Location		
Central City	0.21	0.41
Nonmetropolitan	0.24	0.43
Missing	0.00	0.06
Number of Children		
2	0.38	0.48
3	0.15	0.36
4 or more	0.06	0.24
Family Type		
Single mother	0.19	0.39
Single father	0.05	0.21
Other household with children	0.09	0.28
Household Characteristics		
Any employed in household	0.93	0.26
Any elderly in household	0.04	0.19
Any disabled in household	0.05	0.23
Any noncitizens in household	0.11	0.31

(table continues)

TABLE 1, continued

	Mean	*SD*
Level 2 Variables		
Federal Food Programs		
Food Stamp recipients per 100 poor persons	59.39	15.05
Low-income School Breakfast participants per 100 low-income School Lunch participants	39.10	8.94
Low-income Summer Food Service program participants per 100 low-income School Lunch participants	14.20	9.15
Low-income Summer School Lunch participants per 100 low-income School Lunch participants	4.61	6.36
Economic Policies		
Low-income tax burden	10.48	2.25
Overall tax burden	9.82	1.19
Economic Attributes		
Unemployment rate	4.31	1.04
Poverty rate	11.60	3.23
Average wages per job ($1000s)	31.14	5.88
Median rent ($100s)	5.63	0.99
Social Attributes		
Percentage nonmovers	54.11	5.06
Survey Year		
1999	0.20	0.40
2000	0.20	0.40
April 2001	0.20	0.40
December 2001	0.20	0.40

Note: The means for the Level 1 variables are based on 70,942 households. The means for the Level 2 variables are based on 255 state-year contexts.

accessibility of programs are linked to differences in food security outcomes. We include the following measures:

- Food Stamps: To characterize accessibility of the Food Stamp program, we construct a measure of average monthly number of food stamp recipients divided by number of poor persons.[7] This ranges from 33 to 108 over the 255 state-years included here. Information on number of poor persons comes from the Census Bureau's Small Area Poverty Estimates.

- School Breakfast program: We characterize availability and accessibility of the School Breakfast program by the average number of students eating free or reduced-price breakfast per day for each 100 students eating free or reduced-price School Lunch. Participation in the School Lunch program is frequently used as a benchmark against which to measure School Breakfast participation, because the former is much more uniformly available and more consistently used than the latter. This ratio ranges from 19 to 56 in our sample. Differences in this variable reflect differences in the availability of the breakfast program, as well as differences in the extent to which students participate when the program is offered (see Food Research and Action center, 2002a, for a discussion of program qualities that may affect the attractiveness of the School Breakfast program to students.)

- Summer Meals: Summer meal programs include the Summer Food Service program and the Summer School Lunch program. The former provides meals at a variety of sites that may or may not also provide other programming, and participation is not formally linked to attendance in summer school programs. The latter provides lunches to low-income students attending school programs for the summer. We measure the availability and accessibility of these programs by the average daily participation per 100 participants in the free or reduced-price lunch program during the school year. In our sample, the Summer Food Service ratio ranges from 1.1 to 53.8, and the Summer School Lunch ratio ranges from .5 to 35.4.

There are potential biases associated with these variables. We treat higher participation among eligible families as a proxy for greater program accessibility. However, it is also likely that nutrition assistance programs are more widely used by families with higher levels of need, even after controlling for observable characteristics. If this is the case, our estimates of the relationship between greater program participation and food insecurity would be biased downward, making such relationships more difficult to

[7]This is not intended to be an estimate of the participation rate. Eligibility determination is complex, and some families with incomes above the poverty are eligible for food stamps, while some poor families are ineligible. We do assume, however, that states with higher ratios also have higher true participation rates among eligible families. We further assume that such states have more accessible programs, as per research linking state-specific program characteristics to participation rates (Kornfeld, 2002).

detect. Note, though, that unobserved characteristics that contribute to program participation are only a problem to the extent that they differ systematically across locations.

State Policies Affecting the Resources Available to Low-Income Families. As discussed earlier, we expect food security to be influenced not only by nutrition assistance programs, but also by other kinds of policies that affect resources available to low-income families. As noted above, we focus here on tax policy because of its broad relevance to low-income families.

- Our primary measure is an estimate of the mean percentage of income owed in state and local taxes by families in the bottom quintile of the state income distribution. This is available from the Institute for Taxation and Economic Policy, and is measured for 2002. Because of limitations in data availability, this measure varies by state but not time.[8]

- We also control for the average percentage of income owed in state and local taxes by all families, available from the Tax Foundation. We include this primarily as a control, to insure that any apparent impact of the low-income tax burden is not merely proxying for the overall tax burden.

Economic Attributes of Communities. We expect food insecurity to be lower in states with more favorable economic conditions and a lower cost of living. We include the following measures:

- State unemployment rate: State unemployment rate, available from the Bureau of Labor Statistics, is used to characterize job availability.

- Poverty rate: We expect states with higher poverty rates to have fewer collective resources, and thus higher rates of food insecurity.

- Average wages per job: Mean wages per job are available from the Bureau of Economic Analysis. We treat mean wages as a proxy for job quality in the state.

- Median rent: Median rent, available from the 2000 Census, is used as a partial proxy for local cost of living.

Social Context. We expect less food insecurity when there are stronger bonds among community members.

- We use residential stability, measured by Census data on the percentage of households living at the same address as five years earlier, to proxy for the strength of bonds among community

[8]This measure accounts for state EITC programs. We also experimented with including a separate indicator denoting existence of a state EITC program, but it was not substantively or statistically significant.

members. We expect that the greater the mobility of the population, the weaker the social bonds and the greater the likelihood of food insecurity.

Other. Finally, we include dummy variables denoting survey year to control for unmeasured factors influencing food security that may differ over time. The year variables also control for year-to-year differences in the way households were screened out of the food security questions. Because of these screening differences, the year variables should only be treated as controls, and the coefficients should not be given substantive interpretation.

Predicting State Impacts on Food Insecurity

We are also interested in the additional risk of food insecurity associated with particular states, and in the extent to which these state-specific risks can be explained by observed household and contextual characteristics. We explore this question using the results from our random intercept model (equations 1-2) together with results from two other models—an empty model, which includes a random intercept but no Level 1 or Level 2 variables, and a household-level model, which includes a random intercept and also household-level variables, but no Level 2 variables. The context-specific impact is μ_{0j}, the Level 2 error.

Recall that context-specific intercepts (β_{0j}) and residuals (μ_{0j}) are not explicitly estimated as model parameters. Rather, the model parameters include the mean intercept (γ_{00}) and the variance of the Level 2 residual. For each of the three models, we generate empirical Bayes shrinkage estimates of μ_{0j}. These shrinkage estimates, μ_{0j}*, are estimates of the OLS residual μ_{0j}^ for a particular context, shrunken towards zero, where the shrinkage is proportional to the unreliability of μ_{0j}^.[9] Compared to μ_{0j}^, μ_{0j}* is

[9] The OLS residual is the difference between the within-context estimate of β_{0j} and the predicted value of β_{0j} based on the Level 2 model. In the case of the empty model and household-level model, the Level-2 prediction is simply γ_{00} . In the full model, the Level-2 prediction is based on the characteristics of the particular context. Thus, in the empty model, the OLS residual is the difference between the log-odds of the probability of food insecurity in a given context and the mean log-odds across contexts; in the household-level model, the OLS residual

biased towards zero but has a smaller mean squared error (Snijders and Bosker, 1999). Note that a limitation of this approach is that, the greater the unreliability of $\mu_{0j}{}^{\wedge}$, the greater will be the downward bias in the estimated residuals – what Raudenbush and Bryk (2002, pp.157-158) refer to as 'shrinkage as a self-fulfilling prophecy'. See Raudenbush and Bryk (2002) for a discussion of μ_{0j}* as an estimator of context-specific impacts.

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is the difference between the within-context intercept after controlling for household characteristics and the mean intercept across contexts (γ_{00}); and in the full model, the OLS residual is the difference between the within-context intercept and the predicted intercept based on the specific characteristics of that context. The EB estimator weights the OLS residual by its reliability λ, where $\lambda_j = \tau^2 /(\tau^2 + \sigma^2/n_j)$. Thus, the OLS estimate is given increasing weight when n_j is larger and when the estimated variance of μ_{0j} is greater.